



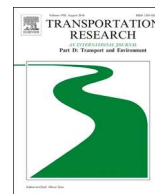
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Spatial associations of dockless shared e-scooter usage

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ABSTRACT

In this study, we explore the usage of e-scooter sharing services in Austin, Texas over about a six-month period. The study is based on trip records of all the shared e-scooter operators in Austin and includes trip start and end locations. We use both analysis of trip patterns and spatial regression techniques to examine how the built environment, land use, and demographics affect e-scooter trip generation. Our findings show that people use e-scooters almost exclusively in central Austin. Commuting does not seem to be the main trip purpose, and usage of e-scooters is associated with areas with high employment rates, and in areas with bicycle infrastructure. People use e-scooter sharing regardless of the affluence of the neighborhood, although less affluent areas with high usage rates have large student populations, suggesting that students use this mode of travel. Implications for planners suggest that better bicycle infrastructure will facilitate e-scooter usage, college towns are a ready market for e-scooter sharing services, and e-scooters may be a substitute for some short non-work trips, reducing car usage, and benefiting the environment.

1. Introduction

New micromobility options, in particular the advent of dockless shared e-scooters are proliferating throughout the world. Their introduction poses challenging questions for cities and transportation planners regarding their usage, their contribution to the transportation network, and their externalities. When and where are they used? Are they used for specific activities? Are they primarily a recreational mode, fun to use but not useful as a substitute for established transportation modes? Do they serve as a last-mile connection to transit? To examine some of these issues we present a comprehensive analysis of spatial factors associated with shared e-scooter usage in Austin, Texas.

E-scooter sharing services were first introduced to the US in September 2017 (Hall, 2017) and in many cities their use exceeds that of bikesharing. Few studies have examined shared e-scooter usage patterns, though the literature is growing. A large literature on bike-sharing serves as a model for how to analyze e-scooters, though usage patterns seem to be very different (Noland, 2019). In contrast to bikesharing, e-scooters do not require physical effort or cycling skills; bike-friendly clothing is also not needed. Usage is more flexible since users are not restricted to pick-up and drops-offs at docking stations, as with most bikeshare services in the US.

An emerging literature on shared e-scooters has focused on travel behavior (Bai and Jiao, 2020; Jiao and Bai, 2020; Mathew et al., 2019; McKenzie, 2019; Noland, 2019; Orr et al., 2019), safety concerns (Allem and Majmundar, 2019; Badeau et al., 2019; Bresler et al., 2019; Mayhew and Bergin, 2019; Sikka et al., 2019; Siman-Tov et al., 2017; Trivedi et al., 2019), and environmental impacts (Hollingsworth et al., 2019).

Travel behavior studies suggest that shared e-scooters are not used as a commute mode (Mathew et al., 2019; McKenzie, 2019; Noland, 2019), or as a last-mile solution (Mathew et al., 2019; Zuniga-Garcia and Machemehl, 2020). For example, in Washington,

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D.C., shared e-scooter usage patterns suggest that usage is for leisure, recreation, and tourism activities, while bikesharing is used for commuting (McKenzie, 2019). Shared e-scooters may satisfy short central city trip needs in Louisville, Kentucky (Noland, 2019) and short-distance errands in Indianapolis, Indiana (Mathew et al., 2019). A study focusing on Austin, Texas, and Minneapolis, Minnesota, suggests that shared e-scooters are mainly being used in city centers and university campuses (Bai and Jiao, 2020). In Austin, Texas, e-scooter usage is correlated with high population density, lower income areas, and areas with higher educational attainment (Jiao and Bai, 2020), as well as those areas with recreational uses (Bai and Jiao, 2020). A major shortcoming of bikesharing is its broad failure to generate trips in low socio-economic areas (Caspi and Noland, 2019). While about a quarter of the docking stations in the US are located in low-income neighborhoods (Smith et al., 2015), dockless sharing is capable of serving the entire city. In some cases, local regulations obligate operators to distribute e-scooters in low socio-economic regions (Orr et al., 2019). A pertinent question is whether dockless e-scooters can better serve low socio-economic communities than docked bikeshare? Interestingly, previous studies concluded that low-income regions generate more e-scooter trips in Austin (Bai and Jiao, 2020; Jiao and Bai, 2020), but not in Minneapolis (Bai and Jiao, 2020), Washington D.C. (McKenzie, 2019), or Portland (Orr et al., 2019).

In this study, we examine the usage of e-scooters in Austin, Texas, one of the three US cities with the most e-scooter usage (NACTO, 2019). Dockless sharing systems were deployed in Austin, Texas, in April 2018 (Spillar, 2018). As of June 2019, seven companies operated about 3400 e-scooters and 8500 supplemental e-scooters in Austin, alongside 550 dockless e-bikes and 500 docked bicycles (“Micromobility | AustinTexas.gov - The Official Website of the City of Austin,” n.d.). As of March 2020, there have been over nine million dockless trips in Austin, and most of them are e-scooters (City of Austin Texas, 2020).¹

Our study focuses on the central part of Austin, as e-scooter trips are clustered there (Bai and Jiao, 2020; Jiao and Bai, 2020). We extend prior work in this area by accounting for spatial correlation in our analysis. We explore how people use e-scooters in different regions of the city, inferring what people use them for, and how the built environment, land use, and other spatial factors influence usage. First, we review the relevant literature. Second, we explain our data sources followed by a discussion of descriptive statistics. We then explain our spatial econometrics methodology. Results are presented and we conclude with a discussion of these results.

2. Literature review

Research into e-scooter travel behavior is limited. However, bikeshare systems can offer some lessons for how e-scooters might be used and how to interpret the data. Substantial research has evaluated the travel behavior associated with these systems, usually by analyzing trip patterns. Commute trips are a common bikeshare trip purpose as are other utilitarian purposes (Fishman, 2016). Spatial analyses show that bikeshare trips are commonly taken from residential areas to commercial areas, central business districts (CBDs), employment centers, and train stations in the morning, and back to residential areas in evenings (El-Assi et al., 2017; Faghih-Imani et al., 2014; Faghih-Imani and Eluru, 2015; Lin et al., 2018; Noland et al., 2016; Sun et al., 2018; Wang et al., 2018). Usage patterns also show a morning and evening peak, reflective of commute trips; weekend usage tends to not show this pattern (Ahillen et al., 2016; Beecham and Wood, 2014; Gebhart and Noland, 2014; Kim, 2018; Mateo-Babiano et al., 2016; Sun et al., 2018; Wang et al., 2018). Most docked systems allow one to either have a subscription (providing various discounts) or can be used in a pay-per-ride (“casual”) fashion. Casual users typically do not seem to follow a daily commute pattern (Ahillen et al., 2016; Kim, 2018).

Dockless bikesharing systems seem to serve a different customer base than docked systems. Trips are shorter than docked bikesharing trips and resemble casual docked bikeshare usage (McKenzie, 2019, 2018). The evidence regarding e-scooters’ trip purposes is mixed, with surveys suggesting that commuting is an important trip purpose, and analyses of trip patterns suggesting otherwise. Commuting is the second most common reported reason for shared e-scooter use in Baltimore, Maryland (25%), after socializing (36%) (Young et al., 2019). Surveys from Denver, Portland, and Baltimore show that commuting and recreation are equally important e-scooter trip purposes (NACTO, 2019). However, overall trip patterns of e-scooters seem similar to trip patterns for casual docked bikeshare users and dockless bikeshare users in studies of Indianapolis, Indiana, Louisville, Kentucky, and Washington, D.C. (Mathew et al., 2019; McKenzie, 2019; Noland, 2019). The discrepancy between survey results and analyses of trip patterns may partly be a function of scale or land use patterns (the systems in Indianapolis and Louisville perhaps differing from systems in larger cities).

Bikesharing is disproportionately used by affluent individuals (Bernatchez et al., 2015; Fishman et al., 2014; Murphy and Usher, 2015). Bikeshare stations in low-income areas are used less than others (Caspi and Noland, 2019; Lin et al., 2018; Ogilvie and Goodman, 2012; Rixey, 2013), and these areas tend to have fewer stations (Goodman and Cheshire, 2014; Smith et al., 2015). In the US, bikeshare users are mainly white, educated, employed, young, and male (Buck et al., 2013; Fishman, 2016; Fishman et al., 2013; LDA Consulting, 2012; Virginia Tech, 2012). E-scooter users may have different demographic characteristics; in Baltimore, the e-scooter sharing participation rate is highest among Hispanics and lowest among African Americans (Young et al., 2019). Seventy-one percent of Portland’s people of color and 74% of the low-income population in the city view e-scooters positively (Orr et al., 2019).

3. Data

The City of Austin provides an open data platform that provides daily updates on dockless e-scooter trips (City of Austin Texas, 2020) in addition to bikesharing trips. Downloadable data includes departure and arrival times, locations (with about 100-meter

¹ Usage has plummeted since Austin implemented a city-wide lockdown in response to the COVID-19 pandemic; usage dropped from about 10,000 trips per day to less than 300.

precision), trip lengths and durations, vehicle type (e-scooter or bicycle), and vehicle ID. Operator and user ID's are not included. We downloaded data on March 27th, 2019.²

The entire downloaded dataset included 3,826,545 dockless trips, 96.1% of which are e-scooter trips. We cleaned the data by removing trips that may have been recorded due to relocation of e-scooters or GPS failure, including trips longer than 80 km or 12 h, trips with an average speed higher than 50 km/h, and trips starting or ending more than 80 km from Austin. Thus, we removed 416,493 e-scooter trips (11.3%). Fig. 1 displays daily trip counts for the data downloaded. For our analysis we only include trips between August 15th, 2018, and February 28th, 2019, excluding trips during the startup of service and during the days around the "South by Southwest" festival in Austin (March 8th – 16th), which were characterized by high usage of nearly 50,000 trips on one day. This leaves us with 2,237,588 e-scooter trips, or 60.8% of the e-scooter trips in the dataset.

To conduct a spatial analysis, we further refined the dataset by overlaying a grid of cells on the point locations. The location coordinates within the data are decimal degrees with three decimal places, and their projection creates a grid of points with a distance of 0.001° (about 100 m) from each other. Based on these points, we created a square grid cell of 0.002° (~200 m), where each cell includes four origin/destination location points. The size of the cells can affect the characteristics of each analysis unit and therefore the results of the analysis – this problem is well known in the science of spatial analysis and is known as the modifiable areal unit problem (MAUP)³. We believe that a 200 m square grid cell is a reasonable trade-off between more precise locations and computational effort, and provides a better representation of the built environment.

Additional spatial data was obtained from the City of Austin, the U.S. Census Bureau, and the State of Texas. From the City of Austin, we retrieved data on land use (City of Austin Texas, 2019a), and street network (City of Austin Texas, 2019b). We used the land use polygons to calculate the proportion of residential, commercial, educational, institutional, industrial, and recreational land uses in each grid cell. Commercial land use includes mixed residential-commercial buildings and thus can account for populated areas as well. We also calculated the land use entropy, a measurement for the diversity of land uses in each grid cell, using an entropy formula: $Entropy = -\sum_k [(p_i)(\ln p_i)]/(\ln k)$ in which p_i is the proportion of each land use and k is the number of land uses measured (Song et al., 2013); scaled from zero to one, this index increases as land use mix increases within a grid cell.

We used the street network to calculate the intersection density, a proxy for shorter paths, on average, between origins and destinations. For each cell, we created a 0.002° (200 m) buffer and divided the number of intersections in the buffer by its area in square kilometers. A buffer is required to more accurately measure intersection densities given the high variability between cells. For example, this is demonstrated in Fig. 2 which shows a cell with no intersections, but many intersections in the surrounding cells. By using the buffer, we calculate that the intersection density is 51.2 per squared kilometer, providing a better representation of the dense grid-like environment of the immediate area.

From the State of Texas, we obtained bus stop locations. We used this data to create a dummy variable that indicates whether there are bus stops in the cell (City of Austin Texas, 2019c). From Open Street Maps (OSM), we retrieved Austin's bicycle network and created a dummy variable to indicate the existence of any bike lane within a cell (OpenStreetMap, 2019). OSM-sourced bikeway datasets have been found to have high concordance with city-provided bikeway datasets in Canada (Ferster et al., 2019), USA, and Europe (Hochmair et al., 2013), and is sometimes more up-to-date than the city's dataset (Ferster et al., 2019).

From the U.S. Census Bureau, we obtained socio-demographic data. The Census Block (CB) and Census Block Group (CBG) polygons were retrieved from Topologically Integrated Geographic Encoding and Referencing (Census Bureau, 2017). From the 2017 American Community Survey (ACS) 5-year estimate we obtained CBG statistics on median annual income by household, total population, and the number of college students (U.S. Census Bureau, 2018). From Longitudinal Employer-Household Dynamics (LEHD) we retrieved the number of employees by CB (US Census Bureau Center for Economic Studies, 2019). We calculated the values of median annual income, population density, student ratio, and employment density for each CB/CBG and gave each cell the value of the CB/CBG it falls in. When a cell overlaid more than one CB/CBG, the value of each CB/CBG was multiplied by its proportional area in the cell. Due to a high correlation between population density and other variables such as student ratio and employment density we decided not to include population density in our analysis.

Finally, we calculated the distance (in meters) of each cell's centroid to the city center. We selected the intersection of Congress Ave. and 11th St. to act as the city center point. Congress Ave. is the main commercial street between the Colorado River and the Texas Capitol grounds. Eleventh St. divides the government district from the downtown commercial district of the city.

The polygon grid that we created includes 17,490 cells over the entire municipal area of Austin. About 62% (10,837) of the cells had no trip origins or destinations in their area, and 2921 (16.7%) cells had less than ten trip departures and arrivals in total. Trips were highly concentrated in the urban core, with about 95% of the trips starting and ending in just 5% of the city area. In our spatial analysis we use only those cells within 0.035° (~3500 m) of our city center point. This includes 7.7% (1342) of the grid cells in Austin with 93% of the trip origins (2,085,731) and destinations (2,079,650), and only 1.5% (20) cells with zero trips. We excluded 16,148 more distant cells with a total of 151,179 (6.8% of all trips) trip origins and 157,002 (7.0%) trip destinations. Sixty-seven percent (10,821) of the excluded cells had no trip origins or destinations between August 16th, 2018 and February 28th, 2019. This was done to minimize issues with excessive zero counts in our data. Thus, our findings are valid for Central Austin and not the entire city.

² In mid-April 2019, the geo-coded location data was removed and replaced with Census tract identifiers for each trip.

³ The modifiable areal unit problem (MAUP) illustrates the possible bias than can be caused by a different division of the same area. Different spatial units (polygons) have different attributes even if they characterize the same region. These characteristics could affect the results which are dependent on the choice of spatial units (Wong, 2009).

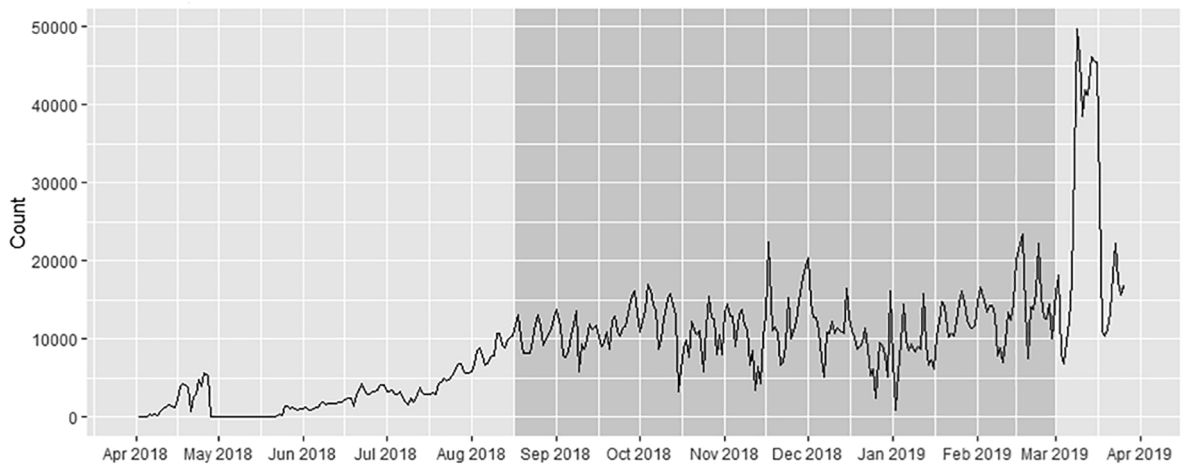


Fig. 1. Daily trip count from April 2018 – March 2019 for shared e-scooters in Austin, TX. The period examined in our study – August 16th, 2018 to February 28th, 2019, is shaded.

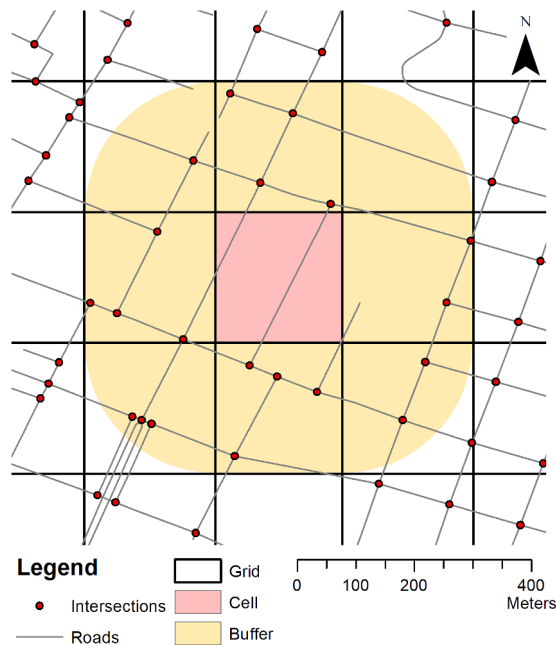


Fig. 2. Intersections in a 200-m buffer around grid cells. The intersection density in the buffered cell is 51.2 intersections per squared kilometer.

4. Descriptive statistics

A summary of trip statistics is shown in [Table 1](#) for trips taken between Aug 16th, 2018, and Feb 28th, 2019. The average number of trips per day is 11,358, with a range between 976 and 23,417 trips per day. On weekends and holidays, the average number of trips was 12,277 trips per day, while during weekdays only 10,895 trips on average were made. Based on vehicle IDs, there were 28,502 e-

Table 1
Summary of trip statistics between Aug 16th, 2018 and Feb 28th, 2019.

	All	Weekdays	Weekends & holidays	Mornings (7 AM–10 AM)	Evenings (4 PM–7 PM)
Trips	2,237,588	1,427,282	810,306	182,005	396,853
Trips %	100%	64%	36%	8%	18%
Avg. trips per day	11,358	10,895	12,277	924	1877
Median trip distance (meters)	971	917	1094	869	996
Median trip duration (minutes)	6.6	5.92	8.58	4.98	6.6

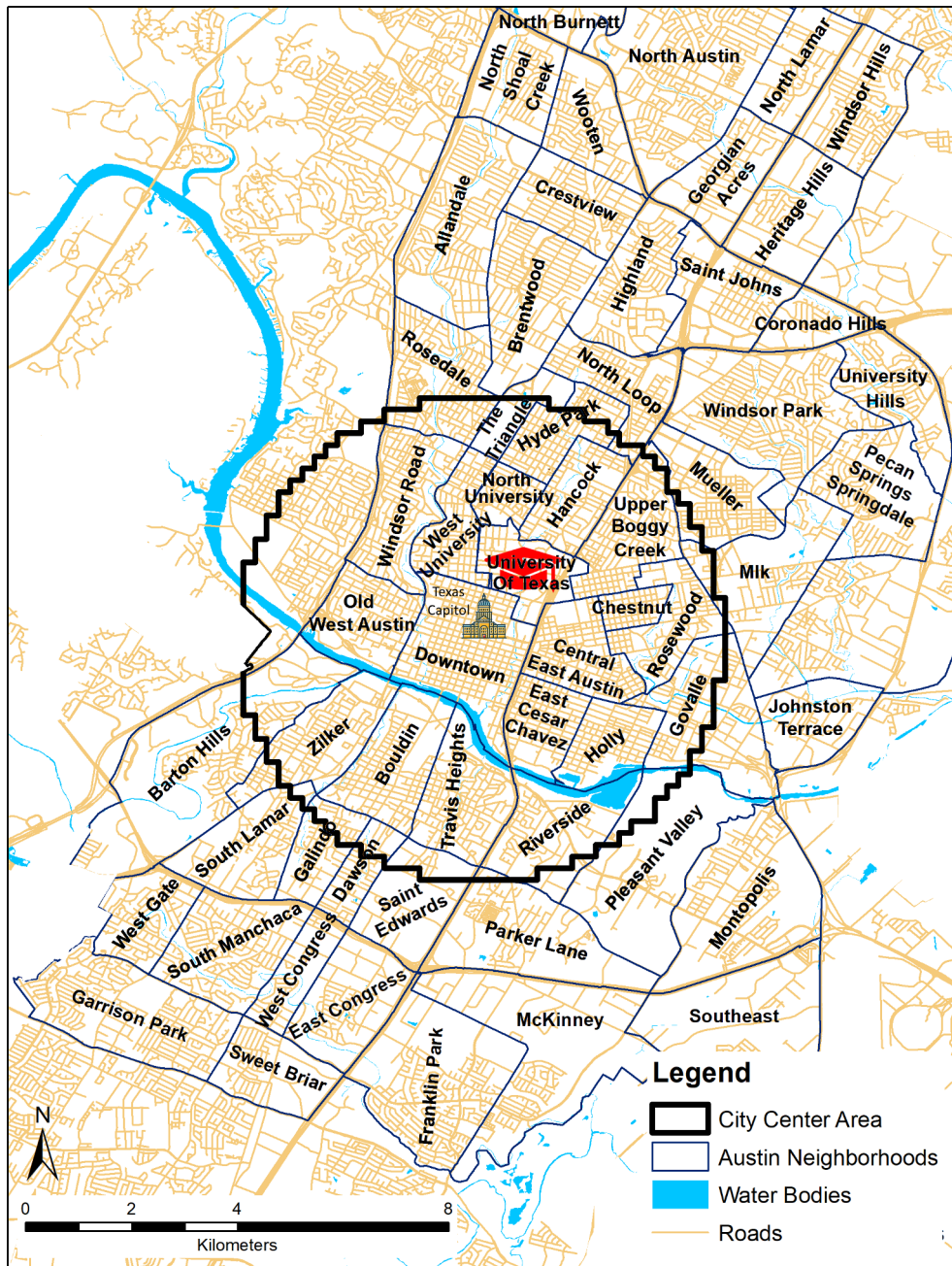


Fig. 3. Neighborhoods in Austin, Texas. Source: City of Austin, Geospatial Services – Data Development.

scooters deployed over this time span. As shown in Table 1, the median trip duration was 6.6 min, the median distance was 971 m, and the median speed was 8.4 km/h.

Hourly trips on weekdays are characterized by a morning peak around 9 AM, a slight decline around 10 AM, and then higher usage rates between 12 PM and 6 PM. These patterns are shown in Fig. 5. Hourly weekend and holiday trip distribution are characterized by one peak around 3 PM. These patterns suggest that shared e-scooters are serving morning commutes, but also many other trips purposes later in the day.

Geographically, there are two areas with substantially higher usage: one in downtown Austin and the other at the University of Texas campus and the adjacent West University neighborhood. High usage is also visible in the area surrounding these areas, in the Boudin neighborhood, Riverside neighborhood, the Mueller neighborhood, and in the Domain mall in north Austin (see Figs. 3 and 6). There are few differences between origin and destination locations. Fig. 6 shows the concentration of trip destinations for all of Austin; the demarcated central area is the focus of our multivariate analysis. This spatial pattern is also valid for weekday, weekend

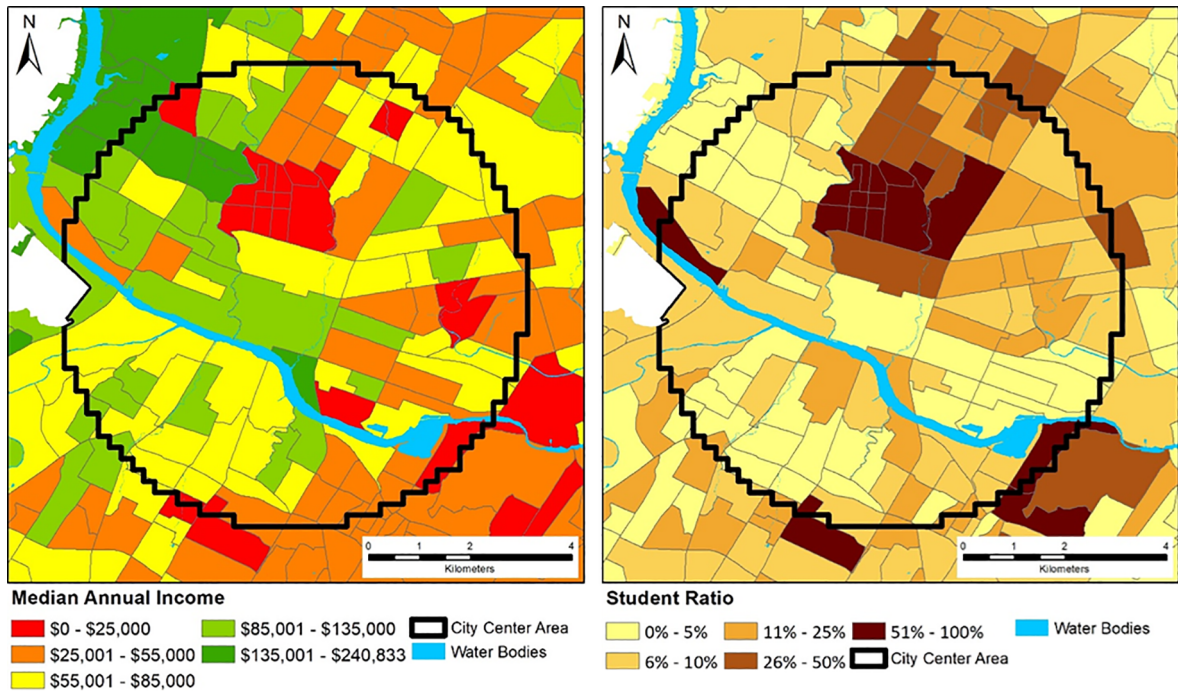


Fig. 4. Median Annual Income and Student Ratio by Census Block Group in central Austin.

and holiday, weekday morning (7AM–10AM), and weekday evening (4PM–7PM) trips.

We show the spatial distribution of two of our demographic variables in Fig. 4. Lower income areas tend to be on the eastern side of the city, with the wealthiest neighborhoods in the northwest. Higher student populations overlap with some of the lower-income areas but are generally near the University of Texas campus. These variables are discussed further in our spatial analysis.

5. Methods

Our key research question focuses on understanding the patterns of e-scooter usage. Are these used for commute trips or recreation? Do they serve various trip types, such as short trips? Consistent with work on bikesharing, our purpose is to explore whether these issues can be determined from trip patterns and spatial analysis.

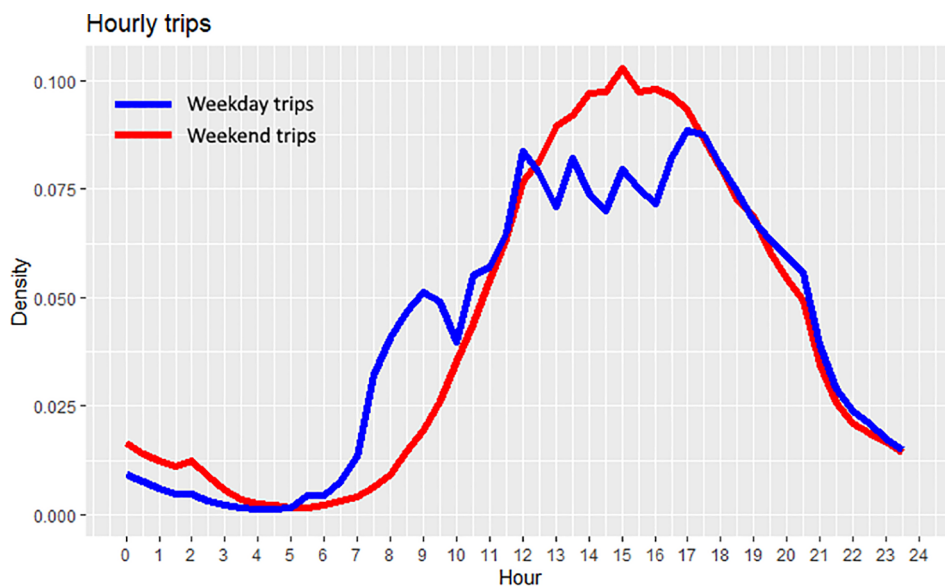


Fig. 5. Hourly trip distribution on weekdays and on weekends/holidays.

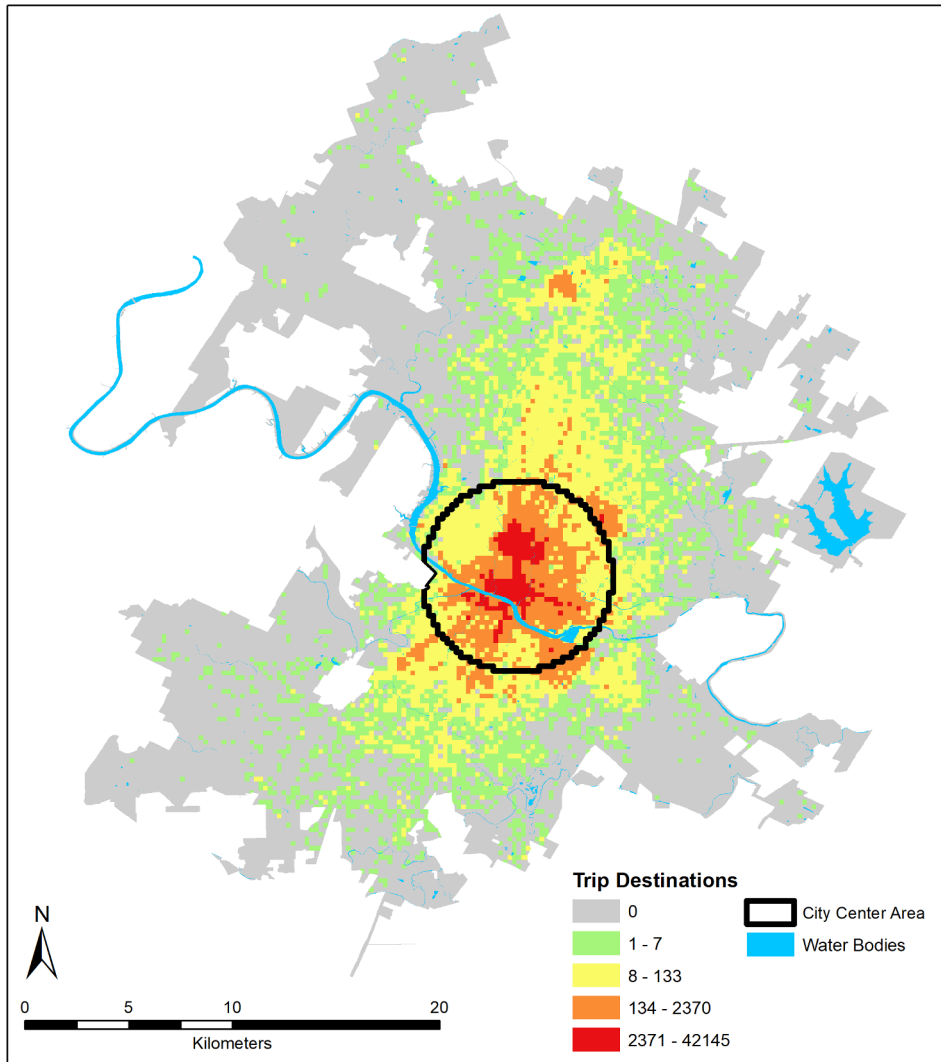


Fig. 6. Trip destinations distribution by 200 sq. meter grid cells in Austin, TX, between August 16th, 2018 and February 28th, 2019. Trip destination classes were determined by ArcGIS – the intervals follow a geometric series to highlight extreme cases and show the variation in the city center.

As previously indicated, we examine the central area of the city. We overlay this with grids and determine the total e-scooter check-outs (departures) and returns (arrivals) in each grid cell. We have 1342 grid cells of 200×200 meters ($0.002^\circ \times 0.002^\circ$), about 40,000 square meters per cell.

A Moran's I test showed that both departure and arrival values are spatially autocorrelated, hence there is a need for a spatial regression to account for unobserved spatial phenomena that are associated with e-scooter usage. We estimated a Spatial Lag model and Spatial Durbin model. In a Spatial Lag model, $y_i = \rho W_{ij}y_j + x_i\beta_k + \varepsilon$, where ρ is a spatial autoregressive coefficient, and W is a spatial weights matrix (Anselin, 2001). In this model, the value of y_i depends on the value of y_j and vice versa. In a Spatial Durbin model, $y_i = \rho W_{ij}y_j + x_i\beta_k + W_{ij}x_j\theta_k + \varepsilon$, where ρ and θ are spatial autoregressive coefficients, and W is a spatial weights matrix. Spatial Durbin models include the spatial effect of the independent variables x_j (Mur and Angulo, 2005). We used a contiguity-based weights matrix which allows bordering cells to influence the outcome variable.

Both the Spatial Lag and Spatial Durbin models are linear models and require a normally distributed dependent variable. Our dependent variable, however, is count data, typically estimated with a Poisson or Negative Binomial model. As previously indicated, we focus only on the central part of the city, thus we remove most cells with zero counts. We add one to each dependent variable and take the natural logarithm of the value, thus approximating a normal distribution, allowing us to estimate linear models. We log-transform the independent variables as well for consistency and ease of interpretation. We add one to the values of variables prior to the log transformation, thus avoiding dropping zero values.

We also estimate Geographically Weighted Regression (GWR) models. This model performs a series of local linear regressions, and provides a unique regression coefficient for each cell in our grid (Fotheringham and Rogerson, 2009). Each local regression includes the cells within a specified bandwidth. We used the ArcGIS Desktop 10.5.1 GWR tool which computes the optimal fixed bandwidth

Table 2
Spatial Lag and Spatial Durbin Log-Log regression results for trip origins.

Dependent variable:	Log of all departure Spatial Lag			Log of all departures Spatial Durbin			Log of morning departures (7 am – 10 am) Spatial Lag			Log of morning departures (7a m – 10 am) Spatial Durbin		
	β			θ			β			θ		
	Coef.	t-stat		Coef.	t-stat		Coef.	t-stat		Coef.	t-stat	
Independent:												
(intercept)	1.566	2.37**		2.423	2.93***		1.754	2.66***		2.593	3.09***	
Log of percent residential land use (0–1)	0.671	2.94***		1.403	4.64***	–1.393	0.364	1.57		1.001	3.22***	–1.319
Log of percent commercial land use (0–1)	0.715	2.06**		1.891	4.45***	–3.100	0.625	1.78*		1.573	3.60***	–2.835
Log of percent institutional land use (0–1)	0.172	0.56		0.042	0.11	0.622	0.92	–0.44		–0.288	–0.72	0.454
Log of percent educational land use (0–1)	0.510	1.84*		0.655	1.74*	–0.186	0.30	0.71		0.138	0.36	0.096
Log of percent industrial land use (0–1)	1.212	2.26**		1.706	2.72***	–1.286	1.004	1.84*		1.521	2.36**	–1.633
Log of percent recreation land use (0–1)	0.335	1.40		0.539	1.75*	–0.661	–0.132	–0.54		0.190	0.60	–0.871
Bikeways in cell (dummy – 0/1)	0.294	5.24***		0.275	4.61***	0.046	0.39	3.81***		0.225	3.68***	–0.032
Log of median annual income (thousands of US \$)	–0.028	–0.79		0.051	0.67	–0.109	–0.062	–1.69*		0.015	0.19	–0.110
Bus stops in cell (dummy – 0/1)	0.507	8.51***		0.513	8.53***	–0.250	0.489	8.08***		0.494	7.99***	–0.146
Log of employment density (employments/sq.km)	0.086	6.22***		0.108	6.48***	–0.016	0.085	6.07***		0.088	5.15***	0.027
Log of intersection density (intersections/sq.km)	–0.013	–0.29		0.334	3.66***	–0.464	–0.064	–1.40		0.157	1.67*	–0.334
Log of entropy (0–1)	0.538	1.63		0.509	1.43	0.993	0.812	2.42**		0.746	2.04**	0.888
Log of student ratio (students/total population)	0.432	2.11**		0.832	1.31	–0.611	0.813	3.79***		0.993	1.52	–0.360
Log of distance to city center (meters)	–0.228	–3.17***		–0.475	–0.82	0.235	–0.243	–3.33***		0.152	0.26	–0.412
rho	0.812	44.25***		0.814	39.76***		0.783	39.16***		0.769	33.11***	
Nagelkerke Pseudo R ²	0.7920			0.8007			0.7840			0.7894		

Note: reference category for land use is “other”; ‘bikeways’ refers to both on-street bike lanes and off-road bike paths; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3
Spatial Lag and Spatial Durbin Log-Log regression results for trip destinations.

Dependent variable:	Log of all arrivals Spatial Lag			Log of all arrivals Spatial Durbin			Log of morning arrivals (7 am – 10 am) Spatial Lag			Log of morning arrivals (7 am – 10 am) Spatial Durbin		
	β			θ			β			θ		
	Coef.	t-stat		Coef.	t-stat		Coef.	t-stat		Coef.	t-stat	
Independent:												
(intercept)	1.501	2.46**		2.326	3.03***		2.593	3.09***		2.022	3.22***	
Log of percent residential land use (0–1)	0.726	3.45***		1.421	5.12***	–1.246	1.001	3.22***		0.148	0.70	–1.456
Log of percent commercial land use (0–1)	0.698	2.18**		1.735	4.44***	–2.674	1.573	3.60***		0.655	2.02**	–2.401
Log of percent institutional land use (0–1)	0.229	0.82		0.161	0.45	0.498	–0.288	–0.72		0.021	0.07	–0.081
Log of percent educational land use (0–1)	0.491	1.92*		0.554	1.60	0.065	0.138	0.36		0.597	2.30**	0.144
Log of percent industrial land use (0–1)	1.140	2.30**		1.544	2.68***	–0.986	1.521	2.36**		0.948	1.89*	–1.743
Log of percent recreation land use (0–1)	0.279	1.27		0.345	1.22	–0.339	0.190	0.60		–0.231	–1.04	–0.629
Bikeways in cell (dummy – 0/1)	0.260	5.03***		0.232	4.25***	0.084	0.225	3.68***		0.200	3.81***	–0.013
Log of median annual income (thousands of US \$)	–0.021	–0.64		0.069	1.00	–0.126	0.015	0.19		–0.061	–1.79*	–0.106
Bus stops in cell (dummy – 0/1)	0.417	7.58***		0.420	7.60***	–0.226	0.494	7.99***		0.354	6.36***	–0.074
Log of employment density (employments/sq.km)	0.074	5.83***		0.095	6.20***	–0.012	0.088	5.15***		0.089	6.85***	0.025
Log of intersection density (intersections/sq.km)	0.007	0.17		0.412	4.93***	–0.523	0.157	1.67*		–0.070	–1.69*	–0.370
Log of entropy (0–1)	0.455	1.49		0.506	1.55	0.638	0.746	2.04**		0.591	1.91*	0.494
Log of student ratio (students/total population)	0.404	2.14**		0.961	1.65*	–0.810	0.993	1.52		0.630	3.22***	0.027
Log of distance to city center (meters)	–0.221	–3.33***		–0.549	–1.03	0.317	0.152	0.26		–0.254	–3.67***	–0.333
rho	0.825	46.82***		0.828	42.33***		0.769	33.11***		0.775	37.90***	
Nagelkerke Pseudo R ²	0.8014			0.8115			0.7894			0.7985		

Note: reference category for land use is “other”; ‘bikeways’ refers to both on-street bike lanes and off-road bike paths; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

length based on Akaike Information Criterion. The bandwidth length used was 3430 m. The GWR model is a more flexible model formulation and provides an interpretation of the variability of coefficient estimates in our study area. We examine how the income coefficient varies across space, providing us with more information on how the income of an area is associated with e-scooter trips.

We model both trip departures (i.e., trip generation) in each cell and trip arrivals. The latter provide a closer link between the user's destination and the associated land use and other spatial features. For trip departures, the user will often need to walk to where an e-scooter is located, leading to less linkage between the spatial factors and the trip starting point, though this would probably be only a minor issue. To obtain a normal distribution we estimated a log-linear model, i.e., the dependent variable is the logarithm of arrivals while the independent variables were not logged.

6. Results

We analyzed data for different times of day, as well as for all trips. There are some minor differences in effect size and significance between the Spatial Lag and the Spatial Durbin models. We present both; however, the Spatial Durbin model has a slightly higher pseudo- R^2 and we focus on those results. Most estimates are similar among the different times of the day and the week, except for our weekday morning commute model (i.e., those trips starting between 7am and 10am). We present results for departures (Table 2) and arrivals (Table 3) for all trips and just morning trips for both a Spatial Lag and Spatial Durbin model.

The proportion of residential, commercial, educational, and industrial land uses within a cell have a positive association with both the number of departures and arrivals in that cell. Compared to the reference category ("other land uses," which includes cemeteries, transportation-related land use, undeveloped land, water, and unclassified land uses), these land uses are associated with more e-scooter trips. The largest coefficients are for commercial and industrial land uses. These results suggest that e-scooters are more likely to be used in these areas, throughout the day. In our Spatial Durbin model, morning departures are associated with residential land uses but not educational land uses. Morning arrivals are associated with educational land uses but not residential.

If there is a bike lane or path within the cell there is a positive association with e-scooter departures and arrivals. When a bus stop is within the cell, there is likewise a positive association. These effects are positive for the model predicting all trips and for the model predicting trips during morning hours. Employment density is also positive and statistically significant in all models. The median income in the cell is not statistically significant for almost all the models; we examine the spatial variation of median income using our GWR model in the next section. Intersection density is significant and positive only in the Spatial Durbin models. Our entropy variable, which represents land use mix, is statistically significant and positive for AM trips only.

We include the fraction of students living in each area, since the University of Texas is a major part of the city center. Students make up about 9.3% of Austin's total population, but about 26 to 31% of the population in the central area. The average of our student ratio per cell is 16.3%. Associations are positive and significant for both all and morning departures in the Spatial Lag model, for all arrivals in the Spatial Lag model, and for all and morning arrivals in the Spatial Durbin model. This does suggest that students are using e-scooters.

We also control for distance from the central point of the city (defined as the intersection of Congress Avenue and 11th Street). Statistically significant effects are found in the Spatial Lag model for all departures and arrivals, with fewer trips as distance to the city center increases. Distance was not significant in the Spatial Durbin models except for the morning arrivals.

6.1. Geographically weighted regression

GWR models estimate the effect of local rather than global independent variable coefficients by including only a limited region for estimating the variable coefficients for each study unit. This can provide some greater insight into the determinants of usage as GWR produces both global and local coefficients, the latter varying by grid cell. We estimated models for two dependent variables – all arrival trips and morning arrival trips. Given the different model formulation, coefficient estimates cannot be directly compared with our Spatial Lag and Spatial Durbin models. We examined marginal effects and found similar results to those in our prior models; these are omitted for brevity and we focus on the spatial distribution of the coefficient estimates.

Among the 14 independent variables included in the GWR model, we present the results for residential, income, and student ratio in Fig. 7. Green shading is for positive coefficient values, while red indicates negative values. Insignificant coefficient values (i.e., $p > 0.05$) are omitted. Residential land use has a positive influence on trip arrivals around the south and the west of the city center, but not in the downtown, the University of Texas campus and its surrounding area. This may imply that people who use the service in this area, do not use it to go home or live in a mixed land-use area, or in mixed-use developments (defined in our dataset as commercial land use). In the morning model, however, residential land use is negatively associated with trip arrivals across the city center.

Income coefficient patterns are generally similar in both models, although income was significant only in the morning arrivals Spatial Durbin model. The central, northern and western parts of the city center are more affluent, and the eastern part is less affluent. In addition, the median income around the University of Texas is very low, while the student ratio is very high. In both models, the e-scooter usage in the northern and western part of the city center is negatively associated with median income – higher income is associated with fewer trip arrivals and lower income is associated with more trip arrivals. The southeast is an exception with higher income associated with more trip arrivals, but not for morning trips.

The coefficient on the fraction of students in the population (student ratio) is relatively similar in both models. The student ratio exceeds 25% around the University of Texas and the northern part of the city center, and also in Pleasant Valley in the eastern part of Riverside. The GWR results show that areas with more students in the northeastern part generate more trips, and areas with fewer

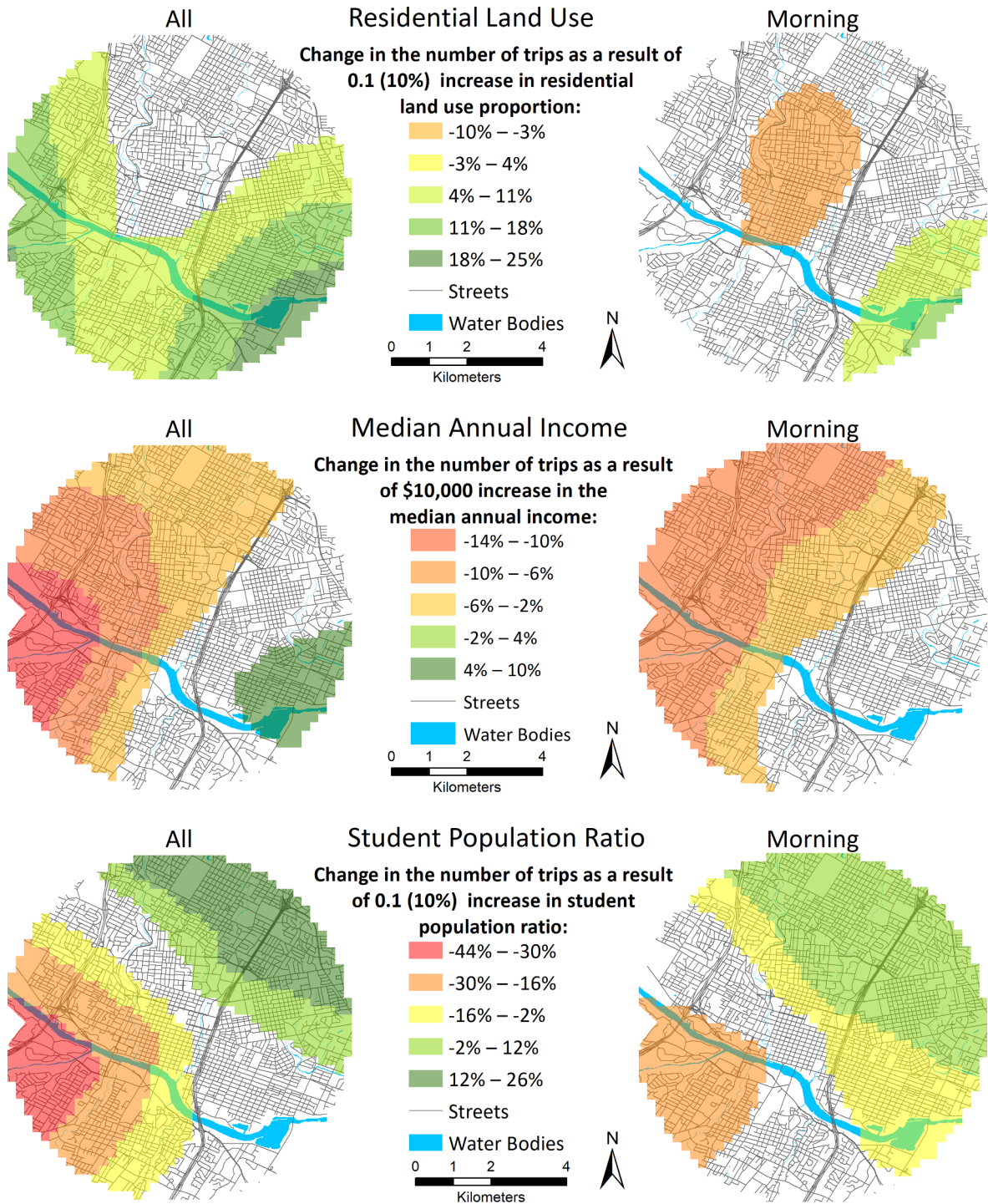


Fig. 7. GWR results for all and morning arrivals. All the presented values are significant ($p < 0.05$).

students in the western part, where the student ratio is relatively low, generate more trips. The difference between the models suggests that students are probably a major source of usage and imply that many of the morning trips are students.

The spatial distribution of other coefficients, not presented in Fig. 7, provide some additional insights. In general, land use variables seems to have greater influence in areas where they are scarcer. This is also true for bikeways, population density, and bus stops, but not for other variables. Unlike the Spatial Lag and Spatial Durbin results, distance from the CBD has a stronger effect for all the arrival trips rather than for morning trips. In both GWR models, distance from the CBD seems to be less important for those using

Table 4

Linear regression results for the GWR income coefficients.

Independent:	Dependent: Income coefficient in GWR Arrivals – all		Dependent: Income coefficient in GWR Arrivals – mornings	
	Estimate	t-stat	Estimate	t-stat
(Intercept)	−2.63E−03	−2.81***	2.59E−03	4.25***
Percent residential land use (0–1)	−4.06E−03	−5.21***	−3.15E−03	−6.21***
percent commercial land use (0–1)	−4.07E−03	−3.16***	−3.99E−03	−4.76***
Percent institutional land use (0–1)	−7.77E−04	−0.67	−1.93E−03	−2.57**
Percent educational land use (0–1)	−1.38E−03	−1.34	−1.68E−03	−2.51**
Percent industrial land use (0–1)	8.55E−03	3.82***	4.19E−03	2.88***
Percent recreation land use (0–1)	−5.25E−03	−6.15***	−3.54E−03	−6.38***
Bikeways in cell (dummy – 0/1)	2.00E−04	0.72	−9.64E−05	−0.53
Median annual income (thousands of US \$)	−3.59E−05	−7.93***	−3.81E−05	−12.93***
Bus stops in cell (dummy – 0/1)	−2.63E−04	−0.89	−6.72E−05	−0.35
Employment density (employments/sq.km)	−4.74E−10	−0.13	−1.32E−09	−0.54
Intersection density (intersections/sq.km)	3.59E−05	5.82***	9.90E−06	2.47**
Entropy (0–1)	3.04E−03	2.44**	1.85E−03	2.27**
Student ratio (students/total population)	−1.46E−03	−1.94*	−3.77E−03	−7.70***
Distance to city center (meters)	6.24E−07	4.01***	−5.79E−07	−5.72***

Note: reference category for land use is “other”; bikeways refers to both on-street bike lanes and off-road bike paths; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the service in the northern part of the city center.

6.2. Variation in the coefficients for income

The GWR analysis indicates that the coefficient estimates for median annual income vary throughout the city. Bikes sharing services have long struggled to serve low socio-economic populations, and cities have had difficulty engaging populations in low-income areas (Caspi and Noland, 2019). The Spatial Lag results show that income is not a significant predictor for general e-scooter sharing trips. However, the influence of income varies throughout the city center and for weekday morning trips. Our GWR analysis allows us to examine the spatial variation in income coefficients; we then regress those coefficients on the same spatial factors to examine how the income coefficient (or sensitivity of response) varies with those factors.

The purpose of this analysis is to determine why there is spatial variation in income coefficients. What are the underlying spatial factors that lead to larger marginal effects in some areas of the city and lower marginal effects (or even negative) in other parts of the city? We are not aware of other studies of shared services examining the source of this variation.

In order to understand what is associated with income having a positive or negative effect on e-scooter use, we regressed the income coefficients of both GWR models. We set insignificant coefficients to zero for this analysis. We used a linear regression with the same independent variables used for the Spatial Lag model, including median income. The results are in Table 4.

All land uses have a negative influence on the income coefficient except industrial land uses, which have a positive influence. In cells with more residential land use, for example, the income coefficient is lower, i.e. lower income is associated with more trips. Income itself also negatively affects the income coefficient – as income in an area rises, the association between income and e-scooter usage becomes more strongly negative. This effect is stronger for all the arrival trips, rather than the morning trips. Entropy positively affects the coefficient; hence, the higher the mix of land uses, the higher the usage in high-income areas. This suggests that high earners in mixed-use neighborhoods are different from high earners in neighborhoods that are more residential in character; the former are more likely to use e-scooters than are the latter, all else equal. We find something similar for students: low-income neighborhoods that are home to a lot of students see more trips than do low-income neighborhoods with fewer students.

7. Discussion and conclusions

Our study examined travel behavior patterns of shared e-scooter use in Austin, Texas. We found that people use e-scooters almost exclusively in central Austin, mainly in and around downtown Austin and the University of Texas, similar to the findings of previous studies (Bai and Jiao, 2020; Jiao and Bai, 2020).

Descriptive data suggest that commuting is not the main trip purpose for shared e-scooter users in Austin. The hourly weekday trip distribution does not show a two-peak pattern, during morning and evening commuting times, but rather displays a long afternoon plateau. Moreover, the average daily usage is higher on weekends and holidays. This suggests that users mainly use e-scooters for purposes other than commuting, similar to shared e-scooters in other cities (Mathew et al., 2019; McKenzie, 2019; Noland, 2019). Other studies have suggested that most trips are recreational (Bai and Jiao, 2020; Mathew et al., 2019; McKenzie, 2019), however we found that e-scooter usage is less likely to start and end in recreational areas, and more likely to do so in residential, commercial and industrial areas.

Usage of e-scooters is associated with areas with high employment rates, and in areas with bicycle infrastructure, compatible with

the findings of many bikesharing studies (Buck and Buehler, 2012; Buehler and Dill, 2016; El-Assi et al., 2017; Faghih-Imani et al., 2014; Faghih-Imani and Eluru, 2015; Fishman, 2016; Heinen et al., 2010; Li et al., 2018; Lin et al., 2018; Mateo-Babiano et al., 2016; Sun et al., 2018; Wang et al., 2018, 2016; Zhang et al., 2017). This implies that more bicycle infrastructure may increase e-scooter usage.

Trip origins and destinations are also associated with bus stop locations, suggesting that people may link e-scooter and bus trips. However a deeper investigation of this matter in Austin found that e-scooter users do not link trips with transit (Zuniga-Garcia and Machemehl, 2020). Income does not affect the general usage but does affect morning trips – the lower the income in the area, the more departures and arrivals take place on weekday mornings. Finally, distance to the CBD matters in the morning models; morning trips are more concentrated around the center of Austin's core.

Results from our models suggest that e-scooter trips are taking place around most types of land uses in Austin, TX. Surprisingly, the many government offices in Texas' capital, represented as “institutional” in our model, did not produce as many e-scooter trips as other places in central Austin.

Many e-scooter operators and advocates wish to encourage increased use among lower-income populations. Our findings show that in central Austin, people use shared e-scooters regardless of the affluence of the neighborhood. This does not provide evidence of who is using e-scooters, but does suggest that they are broadly used throughout different neighborhoods. Our GWR modeling results show that in most of the city center usage is higher in less affluent areas. However, these areas are populated with students who likely have lower incomes, but not low socio-economic status. This point is further strengthened in our analysis of the spatial variation of income's effect on scooter usage; in areas with more students, the association between lower incomes and e-scooter usage is stronger. This suggests that e-scooter sharing services can work well in college towns or on campuses. However, efforts are needed to increase usage in areas with lower incomes.

One limitation is that we do not have information on how e-scooter companies deploy and reposition their fleets. This may affect usage in lower income areas if fewer e-scooters are deployed to these neighborhoods. It would not be unsurprising if e-scooter operators deploy their vehicles in neighborhoods with larger student populations but not in low-sociodemographics neighborhoods, although we have no information or evidence regarding this.

Our study is limited to assessing the spatial patterns and associations of shared e-scooters in Austin. It does not include information regarding users, their demographics, or their motivations. These can only be implied from our data which is aggregate areal demographic data, land use, and median income. Moreover, we cannot assume that users live in the location of their trip origin or destination. This is clearly an area for more research. Other limitations include the spatial accuracy of trip origins and destinations. GPS devices have an accuracy of about 5 m but are not free of errors. While we cleaned our dataset, errors in location data may remain.

Shared e-scooters are a new mode of transportation and if successful can provide an environmentally friendly mode that serves many needs. Our study sheds light on how they are being used in one city, Austin, Texas. Patterns of usage may differ depending on the demographics, road networks, transit availability, and spatial patterns of different cities. Non-commuting e-scooter utilitarian trips appear high in Austin. However, whether shared e-scooters can reduce car usage and benefit the environment is yet to be determined.

Author contribution statement

The authors confirm contribution to the paper as follows: study conception and design: all; data collection: all; analysis and interpretation of results: all; draft manuscript preparation: all. All authors reviewed the results and approved the final version of the manuscript.

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